

Does Life Satisfaction Change in Old Age: Results From an 8-Year Longitudinal Study

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Objectives. The unexpected positive relationship between aging and happiness was called “the paradox of well-being,” which is still a matter of debate. This study examined longitudinal change in life satisfaction (LS) in older adults.

Methods. LS was assessed with the satisfaction with life scale, in a sample of individuals ($N = 899$; aged 62–95 years, at first occasion; $M = 72.73$, $SD = 5.68$) for a period of 8 years (5 waves of data). A multiple indicator (e.g., second order) growth modeling was used to assess change in LS.

Results. Findings from both unconditional and conditional model (in which time-invariant, i.e., age, gender, and education, and time-varying, i.e., self-perceived health, covariates were incorporated in the model) indicated a linear increase in LS for the 8-year period. As expected, the results showed significant random variation in both intercept and slope, indicating that participants start at different levels and change at different rates.

Discussion. Our findings contribute to the debate concerning the paradox of well-being, which calls for explanation. There are few theories that provide some explanation (e.g., the socioemotional selectivity theory). However, to enhance researchers’ understanding of developmental changes that contribute to the paradox of well-being, a more integrative theoretical model is needed.

Key Words: Latent growth modeling—Life satisfaction—Longitudinal—Old—Paradox of well-being.

LIFE satisfaction (LS) is one factor in the more general construct of subjective well-being (SWB). Indeed, according to Diener (1984), the tripartite structure of SWB, which is widely adopted, comprises high LS, high levels of positive affect (e.g., happy, pleased, joy), and lack of negative affect (e.g., angry, depressed). LS constitutes the cognitive dimension of SWB and refers to individuals’ global evaluation of their own lives. It is assumed to be relatively stable because it is assumed to be highly heritable (Lykken & Tellegen, 1996; Tellegen et al., 1988). In order to measure this dimension, Diener et al. (1984) developed the satisfaction with life scale (SWLS). The affective dimension, originating from Bradburn’s (1969) work on happiness, refers to the negative and positive mood in one’s immediate experience. This dimension is defined as emotional well-being, which is assumed to be strongly influenced by daily hassles and uplifts. Cognitive and affective dimensions of SWB are considered as separate (Diener & Biswas-Diener, 2002) but related constructs with a higher correlation of LS with positive affect than with negative affect (for other conceptualizations of SWB, see Busseri and Sadava, 2011).

One of the most important issues in the field of SWB is the relationship between happiness and age. SWB (e.g., LS) is regarded as a key indicator of successful aging. That SWB can support physical and cognitive declines as well as social losses in old age is widely considered as a paradox (Carstensen, Gross, & Fung, 1997; Kunzmann, Little,

& Smith, 2000; Mroczek & Kolarz, 1998). This lack of age-related decline of SWB has been qualified as a paradox because it is intuitively expected that with the increase in risks and losses with advancing age, it becomes reasonably difficult to maintain SWB (Baltes & Baltes, 1990). However, as concluded by Schilling (2006), the paradox in old age may hold only in early old ages, but more research is needed regarding age-related decline in LS for ages more than 70 years. In the same vein, Diener and Ryan (2009) underlined that “while much more research is needed in this area, it is clear that old age is not necessarily a harbinger of unhappiness.” Thus, the purpose of this study was to investigate prospective change in LS among older people.

LS and Aging

Research on stability and change in LS with aging has yielded inconsistent results, in part because of differing approaches used in measuring this construct and in quantifying its change. However, the so-called *paradox of well-being* has been ascertained in numerous cross-sectional (Gaymu & Springer 2010; Hamarat, Thompson, Steele, Matheny, & Simons, 2002; Prenda & Lachman, 2001; Siedlecki, Tucker-Drob, Oishi, & Salthouse, 2008; Stone, Schwartz, Broderick, & Deaton 2010), and, more recently, longitudinal studies (Baird, Lucas, & Donnellan, 2010; Berg, Hoffman, Hasing, McClearn, & Johansson, 2009;

Carstensen et al., 2011; Fujita, & Diener, 2005; Koivumaa-Honkanen, Kaprio, Honkanen, Viinamäki, & Koskenvuo, 2005; Mroczek & Spiro, 2005; Schilling, 2006). For instance, the cross-national study conducted by Gaymu and Springer (2010) revealed that older age predicted increase in LS among European elderly population. Data from a survey of a large representative sample ($N = 430,847$) of the U.S. population, analyzed by Stone and colleagues (2010) revealed that LS had U-shaped age profiles, with a nadir located in the 50s. These authors found linear increases in LS after the age of 50 years, confirming “a striking age and well-being association.”

Researchers have offered various possible explanations as to why aging-related losses do not appear to be accompanied by a reduction in SWB (i.e., positive affect and LS). The selective optimization with compensation theory (Baltes & Baltes, 1990; Baltes, Lindenberger, & Staudinger, 2006; Jopp & Smith, 2006) states that older adults maximize the positive (e.g., gains) and minimize the negative (e.g., losses) affects by selection, optimization, and compensation (Riediger, Freund, & Baltes; 2005; Baltes, 1987). Thus, successful aging entails selective investment in goals and environments and drawing on accumulated expertise to optimize performance in selected domains to compensate for inevitable limitations. In old age, when losses are frequent, it might be of particular importance to maintain growth-related goals for promoting well-being, rather than focusing essentially on losses.

The hedonic treadmill theory (Diener, Lucas, & Scollon, 2006; Diener, Suh, Lucas, & Smith, 1999; Fujita & Diener, 2005; Kahneman, Diener, & Schwarz, 1999; Lucas, Clark, Georgellis, & Diener, 2003) postulates that people have well-being set points to which they inevitably return following adverse life events. According to this theory, the long-term stability in SWB can be accounted for by personality and genetic predispositions rather than by life circumstances (Bartels et al., 2010; Harris, Pedersen, Stacey, & McClearn, 1992; Nes, Røysamb, Tambs, Harris, & Reichborn-Kjennerud, 2006; Stubbe, Posthuma, Boomsma, & De Geus, 2005; Weiss, Bates, & Luciano, 2008).

The socioemotional selectivity theory (Carstensen, Fung, & Charles, 2003; Carstensen, Isaacowitz, & Charles, 1999) postulates that greater emotional saliency will motivate people to regulate their emotions to maintain high levels of SWB. Thus, becoming aware that time is limited, older people direct their efforts toward maintaining emotional well-being and engaging in successful emotion regulation strategies largely than younger adults.

THE PRESENT STUDY

The general pattern of age-related stability of well-being should be qualified. First, it seems that age stability exists for some but not for all dimensions of SWB. Indeed, LS seems to remain stable with age (Baur & Okun 1983; Diener & Suh, 1998; Fujita, & Diener, 2005), and increasing age seems to

be related to high positive affect and low negative affect when functional health is controlled (Charles, Reynolds, & Gatz, 2001; Kunzmann et al., 2000). Second, this pattern seems to happen more in middle aged and young-old than in very old age (Schilling, 2006). For instance, Berg et al. (2009) found that the overall level of LS decreased over 6 years across individuals aged 80 years and older. In one major study of LS applying multilevel models within a longitudinal design, Mroczek and Spiro (2005) found that for a 22-year period, LS increased approximately among participants aged 60–70 years and then declined. More recently, results from a 3-year follow-up study conducted by Enkvist, Ekström, and Elmståhl (2012) revealed that higher age was negatively associated with LS among participants aged 78–98 years. Evidence indicating that distance to death may seriously affect SWB provides some support for this pattern (Gerstorf et al., 2010).

The aim of this study was to contribute to the debate by analyzing prospective data to evaluate whether the “paradox of well-being” applies in advanced age. Our purpose was then to explore the 8-year longitudinal change in LS in old and very old age, using multiple indicator growth models (e.g., second-order latent growth models [2LGM]) incorporating age, gender, and education as time-invariant predictors and self-perceived health (SPH) as time-varying covariate. Figure 1 shows the 2LGM for the final model used to investigate LS in old age. 2LGM, which are an approach to modeling change at the latent level, offer important advantages over the first-order latent growth models (Bollen & Curran, 2006; Ferrer, Balluerka, & Widamen, 2008; Hancock, Kuo, & Lawrence, 2001; Muthén & Khoo, 1998). Indeed, a 2LGM associates a common factor model for the multiple indicators at each measurement occasion with a growth curve model of the common factor scores over time. The second-order factors (i.e., intercept and slope) serve to explain the mean and covariance structure of the first-order factors, which serve to explain the common variation in the multiple indicators. The latent slope factor captures the intra-individual growth (or decline) processes, whereas the latent intercept factor gauges the initial level of the construct under study. Thus, the major advantage of 2LGM approach is that true change is modeled controlling for measurement error. In growth modeling, it is important to ensure that change happens at the level of the construct or latent variable rather than at the level of the observed variables used to measure such a construct. Another major advantage is that the assumption of measurement invariance across time can be tested. This assumption indicates that the construct measured repeatedly retains the same interpretation across waves. The test of this assumption is essential to ensure that it is the outcome of theoretical interest that is changing rather than the scale used to measure the construct. In addition, as with first-order growth models, time-invariant predictors of intercept and slope and time-varying covariates may be incorporated. As shown in Figure 1, as time-invariant predictors, age at baseline, gender, and level of education

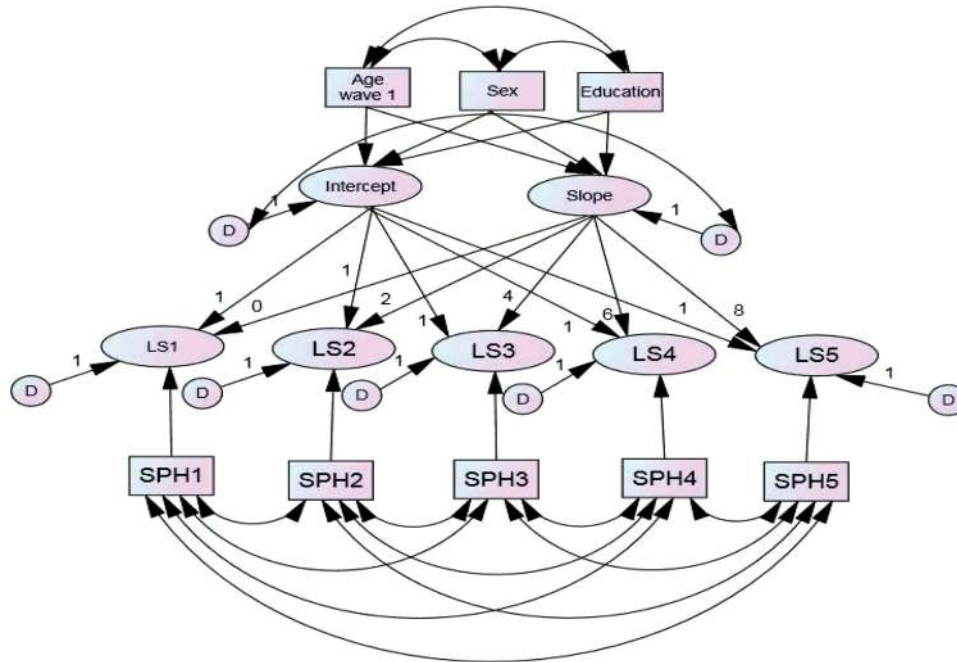


Figure 1. Second-order latent growth modeling (ZLGM) of life satisfaction (LS) change with time-invariant and time-varying covariates. For clarity, are omitted, the covariances between time-invariant and time-varying covariates, the four indicators of each first-order latent variable and their correlated measurement errors. SPH = self-perceived health; D = disturbance.

are modeled on the second-order latent level (i.e., direct effects on intercept and slope) in order to detect systematic inter-individual differences in the individual LS growth curves. In addition, we can investigate if these predictors explain part of these inter-individual differences (see Siedlecki et al., 2008). Gaymu and Springer (2010) found that high level of education predicted increases in LS among older Europeans. Kahneman and Deaton (2010) found that income and education were more closely related to LS than to positive affect. Concerning gender differences in LS, empirical data are mixed: some studies showed higher LS in men (Smith & Baltes, 1998), some other studies showed higher LS in women (Fujita et al., 1991), some studies showed no gender differences (Berg, Hassing, McClearn, & Johansson, 2006; Bourque, Pushkar, Bonneville, & Béland, 2005), and other studies showed varying gender differences across the life course (Shmotkin, 1990). As time-varying covariate, SPH was modeled on the first-order latent level. Thus, SPH assessed at each wave had a direct effect on LS latent construct (i.e., first-order LS factor) of the same wave. Røysamb, Tambs, Reichborn-Kjennerud, Neale, and Harris (2003) found that SWB correlated .50 with SPH.

METHOD

Participants and Procedure

This research used data from an ongoing longitudinal study on “Adjustment to Retirement” initiated in 2001 by a team

of researchers at the University of Tours (France) and which followed up a noninstitutionalized aged cohort of residents from the “Center of France” region. The survey was mailed to participants, who returned the filled questionnaire under a prepaid cover. Data collection were performed every 2 years. Participants were informed of the anonymous character of the study. Thus, anonymity was respected by attributing an identification number to each participant.

The data used in this article were collected at five measurement occasions (with 2-year intervals). Data used in this study were available in 2001 (T1) for 899 participants (57% female; mean age = 72.73, $SD = 5.68$, range = 62–95 years), in 2003 (T2) for 708 participants (58% female, mean age = 74.38, $SD = 5.58$, range = 64–97 years), in 2005 (T3) for 556 participants (58% female, mean age = 76.08, $SD = 5.59$, range = 66–98 years), in 2007 (T4) for 526 participants (58% female, mean age = 77.77, $SD = 5.16$, range = 68–99 years), and in 2009 (T5) for 413 participants (60% female, mean age = 79.40, $SD = 4.99$, range = 70–101 years; see Table 1).

Refusal, low cognitive performance, and death are the common reasons of attrition in prospective studies of older people. However, to investigate the potential impact of attrition, differences on variables used in this study were tested between participants who completed the Time 5 measures and participants who dropped out of the study before Time 5. Participants who dropped out were older ($p = .000$) and less schooled ($p = .019$) than the others. There were no significant differences on LS between participants who completed

Table 1. Descriptive Statistics for Study Measures Across Waves

Measures	Wave 1 (n = 899)	Wave 2 (n = 708)	Wave 3 (n = 556)	Wave 4 (n = 526)	Wave 5 (n = 413)
Age range (years)	62–95	64–97	66–98	68–99	70–101
Mean	72.73	74.38	76.08	77.77	79.40
Standard deviation	5.68	5.58	5.59	5.16	4.99
Life satisfaction					
Mean	20.99	21.02	19.55	21.48	21.35
Standard deviation	4.22	4.32	4.78	4.23	4.14
Cronbach's alpha	0.84	0.86	0.90	0.86	0.85
Self-perceived health					
Mean	3.35	3.36	3.26	3.21	3.23
Standard deviation	0.88	0.89	0.91	0.92	0.91

the Wave 5 assessment and participants who dropped out of the study before Wave 5. More information on the handling of missing data are presented in the “Missing Data” section.

Measures

LS was measured using the SWLS (Diener et al., 1985), which is comprised of 5 items rated in a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The 5 items are as follows: “In most ways, my life is close to my ideal” (ideal), “The conditions of my life are excellent,” “I am satisfied with my life,” “So far I have gotten the important things I want in life,” and “If I could live my life over, I would change almost nothing.” Thus, a higher score is indicative of a high level of LS. Descriptive statistics and reliability coefficients are presented in Table 1.

Time-Invariant Predictors.—Age at baseline (see Mehta and West, 2000, for a rationale for introducing age as covariate), gender, and education level (measured at baseline) were incorporated as predictors to explain individual differences in LS. Also, they served as auxiliary variables to adjust for possible effects of missing data (Enders, 2010; Graham, 2003; as stressed by Graham (2009) “there is no good way of incorporating auxiliary variables into a complete cases model unless they can reasonably be incorporated (e.g., as covariates) into the model of substantive interest” [p. 560].). Previous research has shown them to be important predictors of LS (Diener et al., 1999; Betsey and Wolfers, 2009). Participants’ educational attainment was measured with their responses to an item asking them to select the highest level of education they have reached (ranging from *no schooling* [1] to *university degree* [6]).

Time-Varying Covariates.—Because previous research has consistently found SPH to be associated with LS (Berg et al., 2006; Bishop, Martin, Randall, MacDonald, & Poon, 2012; Bowling, Farquhar, & Grundy, 1996; Borg, Hallberg, & Blomqvist, 2006; Fagerström et al., 2007; Gwozdz, & Sousa-Poza, 2010), perceived health was introduced as time-varying covariate. SPH was evaluated using a single

item, which asked participants to respond to a question regarding their perceived general health (in general, would you say your health is very poor, poor, fair, good, very good? Benyamini, Idler, Leventhal, & Leventhal, 2000; Idler & Benyamini, 1997). The answers to this item range from 1 (*very poor*) to 5 (*very good*). A higher score is indicative of good perceived general health. Although multiple-item scales are advantageous, this single-item measure of perceived health, and highly similar versions, has been used in several studies and has been shown to have acceptable psychometric properties (DeSalvo, Bloser, Reynolds, He, & Muntner, 2006; Jylhä, 2009). For example, to examine the determinants of SPH, Singh-Manoux and colleagues (2006) analyzed two sets of longitudinal data with large samples obtained from the British Whitehall II study and the French Gazel cohort study. They concluded that self-rated health, as measured by a single item, “is a valid measure of health” (p. 370). Indeed, the association between subjective health and objective health is now well established. Based on 180 studies, the meta-analysis conducted by Pinquart (2001) revealed a strong positive association of SPH with objective health (i.e., physical and functional health). This association was found to be even stronger when objective health was measured with symptom checklists ($r = .56-.58$) or by medical examination conducted according to a strict protocol ($r = .53-.57$). Goldberg, Guéguen, Schmaus, Nakache, and Goldberg (2001) examined longitudinal associations (over 6-year period) between SPH (as measured by the widely used single item “How do you judge your current overall health?”) and a large common list of diseases in a large middle-aged cohort. Their findings showed a strong association between SPH and most diseases reported by the participants.

Statistical Analyses

There were two phases of analysis. The first phase consisted of (a) the tests of five CFA models separately for each wave to verify that the unidimensional measurement model of LS is viable at each assessment occasion (i.e., cross-sectional CFAs) and (b) the tests of longitudinal CFAs across all five waves in order to verify that the construct of LS, and its measurement, remain stable over time (i.e., measurement

invariance). The second phase was devoted to the five waves of the 2LGM analysis.

Measurement invariance test is a prerequisite to LGM analysis because the measurement invariance assumption ensures a comparable definition of the latent construct over time. To get an adequate evaluation of change, it is important that the construct under investigation does not have an altered meaning over time. Several points about the procedure used here are worth noting. First, in the longitudinal CFA, we included correlations across time within the same latent factor. Second, same-item residuals were allowed to covary across time to control for error measurement due to the use of repeated measures (Jöreskog, 1979). Third, the steps involved in testing longitudinal measurement invariance of the SWLS were as follows (Brown, 2006): (a) we tested configural invariance, in which none of the parameter estimates was constrained to be the same on different occasions. The aim was to establish that the same factor structure of the SWLS was present at both assessment occasions. (b) To test for weak factorial invariance, we constrained the factor loadings to be the same across time. (c) To test for strong factorial invariance, we added constraints on intercepts by setting them to be invariant over time. (d) Strict factorial invariance was tested by constraining the indicator's error variances to be the same across time.

Analyses of change in LS over 8 years were conducted using latent growth modeling (LGM). A series of unconditional and unconditional 2LGM were developed and evaluated.

Missing Data.—It is obvious that drawing valid inferences from analysis of longitudinal data depends on how the incomplete data mechanism has been measured and included in the appropriate analysis (Jeličić, Phelps, & Lerner, 2009; Schlomer, Bauman, & Card, 2010). Indeed, advances in statistical methodology and computer software have provided robust methods for dealing with missing data in multivariate data analysis (Allison, 2003; Graham, 2009; Little & Rubin, 2002; Raykov, 2005). These “modern” missing data analysis methods, such as full information maximum likelihood-based (FIML) method, preserve the essential characteristics of the data, provide valid statistical inference, maximize the statistical power of the study and its statistical analyses, and avoid bias and instability in the parameter estimates and standard errors for statistical models. Thus, missing data due to attrition were treated in this study using FIML statistical method available in the Analysis of Movement Structures structural equation modeling program (Arbuckle, 2009). FIML maximizes the case-wise likelihood and therefore uses all available information within and across occasions of measurement. For instance, in a growth model, the intercept and slope parameters will reflect both extant and missing data. Although FIML is reported to be less biased than the alternative approaches

(Acock, 2012), bias can be further reduced and statistical power can be boosted by including auxiliary variables in the missing data model (Collins, Schafer, & Kam, 2001; Graham, 2003). Such variables may be included as extra-dependent variables or as correlates of other variables in the model (i.e., saturated correlates model, see Enders, 2010, and Graham, 2003, for details). The saturated correlates approach was used in this study. In addition, according to von Oertzen, Hertzog, Lindenberger, and Ghisletta (2010), the use of multiple indicators (as is the case in this study) increases statistical power to detect variance of slopes in latent growth models.

Fit Indices.—To evaluate the overall fit of the models, we reported the chi-square statistic (a nonsignificant value indicates a well-fitting model) along with the comparative fit index (CFI), the Tucker–Lewis Index (TLI, which yield values between 0 and 1), and the root mean square error of approximation (RMSEA; the closer the RMSEA is to zero, the better the fit) and its 90% confidence interval (90% CI). The advantage of the TLI and RMSEA is that they contain penalties for a lack of parsimony. Hu and Bentler (1999) suggested that to minimize Type I and Type II errors under various conditions, an RMSEA value below .06, and a CFI value of .95 or more together indicate an acceptable model fit. To test for differences in model fit (e.g., tests of invariance), we used the test of small differences in fit along with their statistical power, recommended by MacCallum, Browne, and Cai (2006).

RESULTS

LS Structure in Separate Analyses of Responses From Waves 1–5

Five CFAs were performed to verify the established unidimensional structure of the SWLS at each measurement occasion. Results revealed that this model was not able to fit the data adequately in all waves (e.g., RMSEA values > .06). Modification indices showed that correlation between the unique variances of items 4 and 5 was needed to achieve the models fit. Glaesmer, Grande, Braehler, and Roth (2011) made the same modification to achieve the model fit of the German version of the SWLS. This was also the case for Clench-Aas, Nes, Dalgard, and Aarø (2011) to achieve the model fit of the Norwegian version. Note here that Pavot and Diener (1993) drew our attention that the fifth item of the SWLS (“If I could live my life over, I would change almost nothing”) was the weakest in term of convergence with the other items. A confirmatory factor analysis (CFA) of scores on SWLS in a sample of 818 adults (18- to 94-years-old), performed by Siedlecki and colleagues (2008), revealed that the fifth item had the weakest factor loading. Note also that the fourth and the fifth items of the SWLS refer to the past contrary to the other items, which

refer to the present. Adding the correlation between the residuals of the fourth and the fifth items slightly improved the fit of the five models. However, after deleting the fifth item, the fit of the models was significantly improved (see Table 2). Fit indices were good across all five waves (e.g., TLI = .968–.995, CFI = .994–.999; RMSEA = .071–.022). Factor loadings (range: .67–.90) and uniquenesses (range: .19–.55) were completely satisfactory. Thus, the 4-item SWLS was retained for the subsequent analyses.

Measurement Invariance of the SWLS: Factor Structure Across Multiple Waves

First, a configural invariance model that does not require any of the parameter estimates to be the same across the five waves of data was tested (see Table 3). This model provides a baseline for comparison of increasingly restrictive models that require different parameter estimates to be equal across the different measurement occasions. This unconstrained model yielded a good fit to the data (TLI = .968, CFI = .982, and RMSEA = .038). Second, given evidence of equal factor structure of the SWLS (i.e., unidimensionality) over time, metric invariance model (i.e., weak invariance), in which factor loadings were constrained to be equal over the five assessment occasions, was tested. These constraints did not lead to a significant reduction in model fit (TLI = .968, CFI = .980, and RMSEA = .038). Third, because the indicators showed equivalent relationship to the latent construct of

LS over time, it was permitted to test for strong factorial invariance model, in which equality constraints on the indicators' intercepts were added. These restrictions did not worsen the fit significantly (TLI = .968, CFI = .978, and RMSEA = .038). To test for strict factorial invariance, the equality of the indicators' error variances was added. This restriction resulted in a significant decrease in model fit (TLI = .960, CFI = .970, and RMSEA = .041). Indeed, the test of the small differences between the RMSEA of this model and the RMSEA of the previous model was significant ($p = .038$). This result suggests that each indicator's error variance is not temporally invariant. However, this condition is not as important to the evaluation of measurement invariance as the prior conditions (factor loadings and intercepts; invariance of items' uniquenesses is needed if one wishes to compare manifest scale scores over time (e.g., ANOVA with repeated measures). Marsh, Nagengast, and Morin (2012) stressed that the presence of differences in reliability (as represented or absorbed in the item uniquenesses) could distort mean differences on the observed scores. However, for comparisons based on latent constructs that are corrected for measurement error, the valid comparison of latent means only requires support for strong measurement invariance and not the additional assumption of the invariance of measurement error). Indeed, the invariance of both factor loadings and indicator intercepts (i.e., meaning of the item and its relation to the latent construct) permits to attribute the mean change over time to true change in the construct.

Table 2. Fit Indexes for Confirmatory Factor Analyses (CFA), Invariance Tests, and Latent Growth Models of Life Satisfaction (LS)

	χ^2	<i>df</i>	<i>p</i>	TLI	CFI	RMSEA	RMSEA (90% CI)
Cross-sectional CFAs							
1. Wave 1	11.10	2	.004	.968	.994	.071	(.034–.115)
2. Wave 2	6.29	2	.043	.983	.997	.049	(.008–.094)
3. Wave 3	10.04	2	.007	.973	.995	.067	(.030–.111)
4. Wave 4	2.87	2	.238	.995	.999	.022	(.000–.074)
5. Wave 5	5.67	2	.059	.974	.995	.045	(.000–.091)
Longitudinal CFAs							
M1. Configural invariance	273.30	120	.000	.968	.982	.038	(.032–.044)
M2. Weak invariance	302.11	132	.000	.968	.980	.038	(.032–.044)
M3. Strong invariance	328.41	144	.000	.968	.978	.038	(.042–.043)
M4. Strict invariance	404.93	160	.000	.960	.970	.041	(.041–.046)
Latent growth models							
Unconditional models							
No growth (intercept only)	1750.20	158	.000	.750	.812	.106	(.101–.110)
Linear 2LGM	444.57	154	.000	.953	.966	.046	(.041–.051)
Linear 2LGM with saturated correlates	432.47	154	.000	.941	.967	.045	(.040–.050)
Conditional models							
Linear 2LGM with predictors	494.79	208	.000	.955	.966	.039	(.035–.044)
Linear 2LGM with predictors and time-varying covariates	747.01	303	.000	.942	.957	.040	(.037–.044)

Note. CFI = comparative fit index; CI = confidence interval; *df* = degrees of freedom; TLI = Tucker–Lewis Index; RMSEA = Root mean square error of approximation; 2LGM = second-order latent growth model.

Table 3. Parameter Estimates of the Unconditional 2LGM, 2LGM with saturated correlates, and the 2LGM with Predictors and Time-varying Covariates

	Estimates	SE	<i>p</i> Values
Unconditional 2LGM			
Intercept mean	5.30	0.038	.000
Slope mean	0.011	0.005	.021
Intercept variance	0.998	0.063	.000
Slope variance	0.005	0.001	.000
Intercept–slope correlation	–0.39		.000
2LGM with saturated correlates			
Intercept	5.30	0.038	.000
Slope	0.010	0.005	.040
Intercept variance	1.00	0.063	.000
Slope variance	0.005	0.001	.000
Intercept–slope correlation	–0.39		.000
2LGM with predictors			
Intercept	5.30	0.37	.000
Slope	0.010	0.005	.034
Intercept variance	0.953	0.061	.000
Slope variance	0.005	0.001	.000
Intercept–slope correlation	–0.39		.000
<i>R</i> ² intercept	4%		
<i>R</i> ² slope	2%		
2LGM with predictors and time-varying covariates			
Intercept	5.30	5.30	.000
Slope	0.054	0.054	.010
Intercept variance	0.847	0.847	.000
Slope variance	0.005	0.005	.000
Intercept–slope correlation	–0.45	–0.45	.000
<i>R</i> ² intercept	4%		
<i>R</i> ² slope	2%		

Notes. 2LGM = second-order latent growth model; SE = standard error.

Second-Order Latent Growth Models

Because strong factorial invariance was met in our data, the 2LGM was based on the model in which both factor loadings and intercepts for corresponding variables were constrained to be equal over time. A series of 2LGMs was tested. First, unconditional models (e.g., they do not include any predictors): (a) a no-growth model or strict stability model, which specified that no growth occurred at all over the five time points (Wu, West, & Taylor, 2009); (b) a linear 2LGM, in which growth was modeled across the five waves assuming a linear form with respect to time in years since Wave 1; for this reason, the paths from the slope factor (i.e., basis function) were 0, 2, 4, 6, and 8, respectively. This allows interpretation of slope as per-year change in LS; and (c) a nonlinear 2LGM, in which only the two first slope factor loadings were fixed to 0 and 1, respectively. Freely estimating the remaining three loadings amounts to modeling unspecified trajectories where the shape of the trajectory is allowed to be determined by data (Muthén & Khoo, 1998). In each model, the intercept and slope factors were allowed to covary (i.e., covariance between these factors' disturbances); this accommodate the realistic possibility that LS change over time is related to its initial level assessed at the first time occasion. Second,

conditional models: (a) a 2LGM with baseline predictors (i.e., age at Wave 1, sex, and education) and (b) a 2LGM with predictors (i.e., age, sex, and education) and time-varying covariates (see Muthén & Khoo, 1998), in which SPH assessed at each wave was incorporated as predictor of the latent (first-order LS factor) variable for the same wave (see Figure 1).

Unconditional Models

As shown in Table 2, the no-growth model yielded a very poor fit to data by the conventional standard of goodness-of-fit criteria: TLI = .750, CFI = .812, and RMSEA = .106. The nonlinear growth model results were problematic, as the solution was improper (i.e., the covariance matrix between intercept and slopes factors was not positive definite; we attempted to perform a quadratic 2LGM; however, this model did not converge in a proper solution). The linear 2LGM model fit the data well: TLI = .953, CFI = .966, and RMSEA = .046. The parameters of greatest interest, those relating to the latent growth structure were statistically significant (see Table 2). First, significant mean levels existed for LS intercept, $M = 5.30$, $p = .000$ and slope (growth across 8 years), $M = .011$, $p = .024$. These findings indicate that, at the group level, there was a significant increase (positive linear slope) in LS from Wave 1 to Wave 5. Second, there is a significant amount of variability in the intercept factor (.998, $p = .000$), indicating that the participants do not start with the same level of LS. In addition, the variance in the slope factor was statistically significant (.005, $p = .000$), indicating a significant variation among the elderly population in their trajectory from Wave 1 to Wave 5. Third, the correlation between the intercept and slope was negative (–.39). This moderate, but statistically significant ($p = .000$), value suggests that individuals with higher levels of LS at baseline tend to have slower rates of change as they age.

Saturated Correlates Model

Gender, age, and education were incorporated as auxiliary variables into the unconditional model. Auxiliary variables should be chosen to reflect possible differences among respondents with complete data and missing data (Graham, 2009). However, as noted by Enders (2006) “it may not be possible to identify useful auxiliary variables with any degree of certainty, but the inclusion of extra “junk” variables does not appear to negatively affect estimation” (p. 430). Thus, if the missingness is related to any of the auxiliary variables, then adding those variables would result in different parameter estimates. In order to specify the model, we followed Graham's (2003) approach, which relies on three rules: an auxiliary variable must be correlated (a) with all other auxiliary variables, (b) with all exogenous predictor variables (if present in the model), and

(c) with the residuals of any observed endogenous variable (e.g., indicators of latent variable).

As shown in Table 2, the saturated correlates model yielded the same fits as the unconditional model. As can be seen in Table 3, incorporating gender, age, and education as auxiliary variables into the 2LGM unconditional model did not result in different parameter estimates, that is, intercept mean, slope mean, intercept variance, and slope variance. Hence, we can conclude that missingness was not related to these variables, which will be used as predictors in subsequent analyses.

Conditional Models

After identifying the best-fitting unconditional latent growth model (2LGM) for LS, and given that the unconditional model suggests that there is predictable inter-individual heterogeneity in change trajectories, we examined two conditional models. First, we tested a 2LGM incorporating sex, education, and age at baseline as correlated time-invariant predictors of change. Each predictor variable exerted an effect on both intercept and slope factors associated with LS. Thus, the residuals associated to the intercept and slope factors, represent the adjusted values of factor intercepts and slopes after partialing out the linear effect of the predictors of change. As shown in Table 2, this model demonstrated a very good fit to the data (TLI = .955, CFI = .966, and RMSEA = .039). The parameter estimates obtained from this model are presented in Table 3. It should be noted that none of the covariates were found to have a significant effect on rate of change in LS (i.e., slope factor). However, only sex ($\beta = -.17, p = .000$) and education ($\beta = .08, p = .030$) showed significant effects on initial level in LS (i.e., intercept factor). Given a coding of “1” for men and “2” for women, these findings suggests that LS, on average, was lower at Wave 1 for women than it was for men. Level of education was found to be a positive predictor of initial level in LS. In sum, the three covariates explain 4% of the variance in the initial level status and 2% of the variance in the growth rate. Second, we tested a 2LGM with predictors and SPH as time-varying covariate at each wave. As indicated in Table 2, this model fit the data well (TLI = .942, CFI = .957, and RMSEA = .040). As in the precedent model, only sex and education showed significant effects on the initial level of LS. None of the covariates was found to have a significant effect on rate of change in LS. SPH (introduced as time-varying covariate) was found to be a significant predictor of first-order LS latent factor (β ranged from = .10, $p = .005$ for self-rated health at Wave 3 on LS latent factor at Wave 3, to .26, $p = .000$, for self-rated health at Time 4 on LS at the same time).

DISCUSSION

This study contributes to the debate concerning the paradox of well-being (Mroczek & Kolarz, 1998), referring to the

unexpected positive relationship between age and happiness. Because aging is typically associated with multiple losses and decline in physical health, early research inferred that it is particularly difficult for the elderly population to maintain their SWB (e.g., Wilson, 1967). However, even under unfavourable situations, the elderly population can contemplate their life in a satisfactory way. LS change has mainly been investigated in cross-sectional settings (e.g., Realo & Dobewall, 2011). So far, longitudinal studies on age-related differences or change in LS are rare. Thus, the paradox of well-being needs further empirical evidence, especially in the very old age (Schilling, 2006).

To the best of our knowledge, this study is the first investigation that sets out to examine change in LS in a sample of individuals aged between 62 and 95 years for a period of 8 years, using a multiple indicator (e.g., second-order) growth modeling. As stated by Hancock, Kuo, and Lawrence (2001), multiple indicator growth modeling “offers the advantage of creating a theoretically error-free construct for growth modeling rather than using error-laden variables or their composites.” Consequently, it is possible to separate change in LS that is due to measurement error from true change in LS. In addition, the use of multiple indicators increases the statistical power to detect variance of slopes in latent growth models (von Oertzen et al., 2010). Let us, then, summarize our main findings.

First, the results of this study provide evidence of a significant change in LS in old age. Indeed, the no-growth (i.e., intercept only) model failed to fit the data, indicating that the assumption of stability in LS among the elderly population was not tenable in our study.

Second, a linear growth pattern seems to be a realistic representation of change in LS among the elderly population. Controlling for age, gender, education, and SPH, the positive value of the growth rate indicated a linear increase for the 8-year period. Although the nonlinear growth models did not converge, this finding clearly supports the paradox of well-being in later life, summarizing the idea that aging does not make people less happy. It is consistent with recent findings revealing that older age predicted increase in LS among both European and American elderly population (Gaymu & Springer, 2010; Stone et al., 2010). For instance, data from a survey of a large representative sample ($N = 430,847$) of the U.S. population, analyzed by Stone and colleagues (2010) revealed that LS had U-shaped age profiles, with a nadir located in the 50s. They found linear increases in LS (as assessed with an 1-item scale) after the age of 50 years, which is characterized by these authors as “a striking age and well-being association.” The paradox of well-being calls out for explanation (Whitbourne & Sneed, 2002). As we mentioned earlier, theoretical models most frequently cited to explain this paradox are the model of selective optimization with compensation (Freund & Baltes, 1998, 2002), the hedonic treadmill model (Diener et al., 2006), and the socioemotional selectivity model

(Carstensen et al., 2003, 2011). The latter model, which is increasingly cited in the gerontological research and literature, emphasises the role of perception of time in the selection and pursuit of social goals. Older individuals, because of their relative proximity to death, perceive their time as limited. Therefore, their goals focus around social relationships that are more gratifying and enjoyable as well as activities that seem more meaningful, consistent with their prevailing motive to improve their emotional experience (Holahan, Holahan, Velasquez, & North, 2008). Happiness seems to be a vital imperative in the face of threat of death, but there is a limit to happiness. Indeed, distance to death seems to affect SWB seriously (Gerstorf et al., 2010). Using 22-year longitudinal data from deceased persons aged 70- to 100-year-old, Gerstorf and colleagues (2008) found that individual differences in late-life intra-individual changes in LS were better described using a distance-to-death rather than a distance-from-birth time (i.e., chronological age). Thus, the burdens associated to approaching death make it increasingly difficult to maintain SWB.

There are other noteworthy theoretical models that may help understanding the paradox of well-being. Erikson's theory of psychosocial development is one of them. According to Erikson's (1963) stages of human psychosocial development, older people have to face a nagging ontological crisis: ego-integrity versus despair. During the last stage of development, old individuals develop feelings of contentment and integrity if they believe that they have led a happy, productive life. They may instead develop a sense of despair if they look back on a life of disappointments and unachieved goals (Sneed, Whitbourne, & Culang, 2006). Happiness seems to be ontologically linked to ego-integrity development.

The model of strength and vulnerability integration (SAVI), proposed by Charles (2010), is another heuristic framework for explaining factors that influence emotion regulation and SWB across adulthood and aging. SAVI posits that aging is associated with strengths in emotion regulation that involve the use of attentional, appraisal, and behavioral strategies of emotion regulation.

Taylor and Brown's (1988) social psychological model of mental health provides another interesting perspective, which may partly explain the paradox of well-being. This model assumes that having positive illusions (i.e., beliefs) is associated with increased happiness. Individuals adapt to adversity even to the point of distorting reality. For instance, aged people will often express satisfaction with poor living conditions. There is now considerable literature on how older people maintain positive self-evaluation in the face of threats, for example, making advantageous social comparison and attributing failures to external causes. One might therefore wonder whether satisfaction with life is on its own a positive illusion, defined as the pervasive tendency to see oneself in the best possible light (Taylor & Brown, 1988).

Finally, from the perspective of aging self-concept, the paradox of well-being could be interpreted as a

manifestation of the "ageless self" (Kaufman, 1987) in which individuals strive to stay outside of the aging process. It serves to enhance the continuity and coherence of the self-image marred by the physical changes associated with age, which are almost uniformly perceived as negative. Whitbourne (1998) argued that adults at all ages wish to see themselves as loving, competent, and good.

We should note here that these models and theories are not mutually exclusive and each may be partially correct or simply incomplete. Thus, to enhance researchers' understanding of developmental changes that contribute to the paradox of well-being, a more integrative theoretical model is needed.

Third, as expected, linear growth in LS was not homogeneous among our participants, meaning that they do not grow at the same rate. Indeed, the standard deviation of the growth rate (equal the square root of the slope variance = 0.07) was larger than the mean of this growth rate (0.01), indicating that rates of change for some individuals are positive, whereas for others they are negative. And, as indicated by the significant negative covariance between LS intercept and slope, individuals initially higher in LS (at Wave 1) experienced slower increases in LS over time relative to individuals with initially lower levels of LS. Because prospective studies examining long-term trajectories of LS are scarce and because these studies have used different measures of LS, and different statistical analyses, the comparability of the results is therefore difficult. For instance, in their prospective study over a 22-year period, Mroczek and Spiro (2005) used first-order growth curve modeling to examine change in LS as assessed with Liang's (1984) 11-item version of the LS Inventory. Recall here that first-order growth models repose on composite scores that incorporate the variables' measurement errors. Results of this first-order growth model revealed that LS increased to approximately 65–70 years and then declined. However, decreases in satisfaction were slight, such that the oldest adults reported satisfaction similar to that of the 40-year-olds and near the lower levels reported by people in their late 20s. Fujita and Diener (2005) analyzed 17-year follow-up data based on an 1-item scale ("How happy are you at present with your life as a whole?" on a 0 (*totally unhappy*) to 10 (*totally happy*)). They found that there is modest stability in LS and that 24% of participants do change significantly and substantially in LS.

Fourth, SPH, used as time-varying covariate, was found to be a significant predictor of LS at each assessment point. This finding is not surprising since health has been shown to be a key determinant of SWB (Palmore & Kivett, 1977). For example, analyzing a 16-year longitudinal data from a large sample, Lacruz, Emeny, Baumert, and Ladwig (2011) found that increased net income, good self-rated health, good health status, and social support along with low levels of somatic complaints were independent determinants of higher LS. However, this finding should be interpreted in

light of limitations of correlation-based analysis (i.e., SEM) used in this study. Indeed, the relationships between physical health and SWB are still a matter of debate (Aspinwall & Tedeschi, 2010; Coyne & Tennen, 2010). For instance, Diener and Chan (2011) stated that “a strong case, but perhaps not an airtight case, can be made that SWB causally influences health and longevity.”

Fifth, sex, age, and level of education, measured at Wave 1, failed to predict change in LS. These prospective predictors explained 2% of variation in LS changes for an 8-year period. This finding suggests that many more other covariates are needed to explain the growth rate variation in LS across aged people. The meta-analysis of prospective studies evaluating changes in cognitive well-being (i.e., LS) and affective well-being (i.e., positive affect) after major life events (e.g., marriage, retirement, bereavement), conducted by Luhmann and colleagues (2012), revealed that most events had stronger and persistent effects on LS than on positive affect. Thus, LS changes over time and life contingencies (Lucas & Donnellan, 2007). Lachman, Rosnick, and Röcke (2009) found that control beliefs play a significant role for maintaining LS in later life in the face of declining health and other losses (see also Berg, Hassing, Thorvaldsson, & Johansson, 2011). Li and Liang (2007) found that links between social exchanges and LS could grow stronger in advanced old age in the context of functional decline and increasing dependence on social network.

This study must be interpreted in light of its limitations. First, despite the longitudinal nature of the data set, the models tested in this study do not necessarily represent causal relationships between the variables included into these models. Indeed, structural equation modeling is a correlation-based technique, and hence does not allow us to make any confident causal inferences about the relationships among variables (see Pearl, 2000). The second limitation of this study is the generalizability of its results. Indeed, as these findings are based on a nonrepresentative sample, they should not be generalized to all older people, nor they could be transferred to other different cultures. Future prospective research should examine SWB among older people in countries from more diverse cultural contexts, such as Asian and African cultures (Kamilar, Segal, & Qualls, 2000; Schimmack, Radhakrishnan, Oishi, Dzokoto, & Ahadi 2002). Missing data, which is more common in prospective research among older people, is another limitation. In fact, the modern intent-to-treat approaches (e.g., FIML) try to prevent but cannot eliminate completely the serious threats to internal (e.g., statistical power) and external (e.g., generalizability of findings) validity due to missing data. In addition, it is important to note that the missing data corrections assume that data are missing at random. Consequently, the analysis does not eliminate completely the possibility that there is a nonignorable sample selection bias in our data. The fourth limitation is with regard to the measurement of SPH. Indeed, the

assessment of SPH with an 1-item question is also disputed. However, previous prospective studies have demonstrated the validity of this widely used single item (Goldberg et al., 2001; Singh-Manoux et al., 2006). For example, the results from meta-analysis of the association between a single general self-rated health item and mortality showed a significant relationship between worse SPH and an increased risk of death, even after controlling for functional status, depression, and comorbidity (DeSalvo et al., 2006). Also, although SPH showed strong relationships with objective health, its accuracy is not as high as data from medical examinations. Future research should include informant-based measures and additional objective measures of physical health.

To conclude, despite these limitations, this study has some strengths. The sample size remained large at Wave 5 ($n = 413$), allowing to take advantage of current advances in LGM techniques, which are well-known for their stringent data requirements. Thus, the findings of this study have considerable implications regarding issues of happiness in old age. In longer and healthier lives within the western societies, the role of happiness is a matter of debate. However, further prospective research using the same measure and statistical analyses is needed to confirm our findings. Future prospective research should focus on the ecological influences on LS change in old age.

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